Neural Network Based Noise Identification in Digital Images

Karibasappa K.G[1], Shivarajkumar Hiremath[2], K. Karibasappa[3]
[1,] B.V.B.College of Engg. &Tech.,Hubli-31
Email: Karibasappa_kg@bvb.edu
[2] B.V.B.College of Engg. &Tech.,Hubli-31
Email: shivaraj2323@gmail.com
[3] Dayanand Sagara College of Engineering and Tech., Bangalore
Email: k_karibasappa@hotmail.com

Abstract: **Image noise is unwanted information in an image and can occur at any moment of time such as during image capture, transmission, or processing and it may or may not depend on image content. In order to remove the noise from the noisy image, prior knowledge about the nature of noise must be known otherwise noise removal causes the image blurring. Identifying nature of noise is a challenging problem. Many researchers have proposed their ideas on image noise identification and each of the work has its assumptions, advantages and limitations. In this paper, we proposed a new methodology based on neural network for identifying the different types of noise such as Non Gaussian, Gaussian white, Salt and Pepper and Speckle noise.**

***Index Terms*— Image noise, PNN, kurtosis, skewness**

I. Introduction

Image noise is the random variation of brightness or color information in images produced by the acquisition process due to camera quality, acquisition condition, such as illumination level, calibration and positioning or it can be a function of the scene environment. Presence of noise is manifested by undesirable information, which is not at all related to the image under study, but in turn disturbs the information present in the image. So elimination of noise is one of the key research work to be done in computer vision and image processing as noise leads to the error in the image. Accordingly there are different categories of noise present such as gaussian noise, non gaussian noise, speckle noise and salt-pepper noise, film grain noise, thermal Noise, photoelectron noise. Many papers are published to illustrate the techniques for image noise identification and classification [1]. But most of the researchers have used the simple conventional method. Here we are proposing the technique for image noise identification using Probabilistic Neural Networks. A wide variety of image de-noising algorithms have appeared in the literature. In general, they perform quite well, but almost all of them focus towards reduction or removal of a specific type of noise, such as, non-gaussian or gaussian white noise [2], speckle noise [3] and impulsive (or, salt-and-pepper) noise [4]. Although these techniques are very useful for applications where manual image de-noising is acceptable they fall short of their goals in many other applications that call for automated image restoration. In response to these automated techniques, identification of image noise is of considerable interest, because once the type of noise is identified from the given image, an appropriate algorithm can then be used to de-noise it. Also, since poor de-noising often results from poor noise identification, a better noise identification technique is always preferred. In the literature we found different image noise identification techniques namely noise identification techniques based on statistical parameters[5], noise identification techniques based on soft computing approach[6] , noise identification techniques based on graphical methods [7] and noise identification techniques based on gradient function methods [8]. In the literature we found different image noise identification techniques namely noise identification techniques based on statistical parameters[5], noise identification techniques based on soft computing approach[6] , noise identification techniques based on graphical methods [7] and noise identification techniques based on gradient function methods [8].

A. *Probabilistic Neural Network(PNN)*

Probabilistic Neural Networks (PNN) [9] is feed-forward neural networks that can be used as general purpose classifiers. PNNs were proposed by Specht in 1989, it is a type of Radial Basis Function (RBF) network which is suitable for pattern classification. The PNN classifier is basically a classifier, of which the network formulation is based on the probability density estimation of the input signals. Probabilistic Neural Networks (PNN) estimate the probability density function for each class based on the training samples. PNNs have gained attention because they offer a way to interpret the network's structure in the form of a probability density function and their performance is often superior than other classifiers. Because of ease of training and a sound statistical foundation in Bayesian estimation theory, PNN has become an effective tool for solving many classification problems. Finally, the problem is formulated to identify the type of noise from the observed image, where the main goal is to identify the nature of noise present in images using probabilistic neural network.

II. METHODOLOGY

In principle, the noise identification method proposed here consists of three key steps:

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Step 1. Extract some representative noise samples from the given noisy image,
Step 2. Estimate some of their statistical features, and
Step 3. Use a probabilistic neural network to identify the type of noise.
The architecture design for our proposed method is as shown in figure 1.

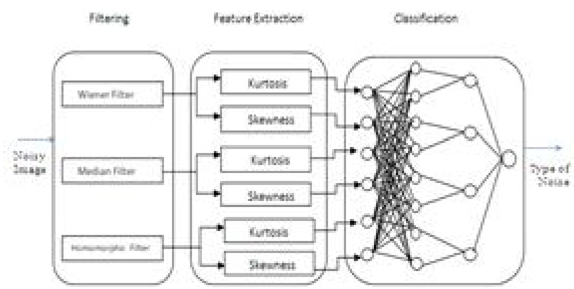

Figure 1. Architecture Design of Proposed Method

It consists of three key steps: filtering, feature extraction and classification. Filtering is done to get different noise samples from the given input noisy image. The given input noisy image is applied with three filters namely wiener filter, median filter and homomorphic filter to get three noise samples. Filtering is followed by feature extraction in which we are extracting the features called kurtosis and skewness. Since we get three noise samples from the filtering step, totally we will get three values of kurtosis and three values of skewness. These six values are given as input to the probabilistic neural network. The network is trained to identify the type of noise that affected the image. The algorithm for the proposed method can be given as below:
Input: Grayscale Noisy image
Output: Statistical Parameters and Type of Noise
1. Take the noisy image as an input.
2. Generate the training data set sequences.
3. Apply the three selected type of filters to the noisy image to get the estimates for the original image.

$\hat{y}_{wiener}(i,j) = f(i,j) * H_{wiener}(i,j)$
$\hat{y}_{median}(i,j) = f(i,j) * H_{median}(i,j)$
$\hat{y}_{homo}(i,j) = Exp\,[\log(f(i,j)) * H_{Wiener}(i,j)]$

4. Get the three noise estimates based on the output from the three filters.

$\omega_{wiener} = f(i,j) - \hat{y}_{wiener}(i,j)$
$\omega_{median} = f(i,j) - \hat{y}_{median}(i,j)$
$\omega_{homo} = f(i,j) / \hat{y}_{homo}(i,j)$

5. Calculate the statistical parameters such as kurtosis and skewness.
6. Identify the type of noise using neural network.

The above steps can be summarized as follows.
Assume the original *MxN* image *y (i, j)* is contaminated by some type of noise, $\omega(i,j)$. The observed image *f(i, j)* can be modeled by either equation (1) for additive noise, or equation (2) for multiplicative noise:

$$f(i,j) = y(i,j) + \omega(i,j), \quad 1 <= i <= M,\ 1 <= j <= N \qquad (1)$$

$$f(i,j) = y(i,j)\,\omega(i,j), \quad 1 <= i <= M,\ 1 <= j <= N \qquad (2)$$

To start with, we first assume that the type of noise is unknown, but it belongs to one of N known classes. For each type of noise, we choose a simple linear or nonlinear spatial filter operator capable of removing most of the noise of this type from the image. Suppose H_k *(i, j), 1d” k d” N*, denote these filter operators. To extract some noise samples, first process the image through each filter operator to obtain:

$$g_k(i,j) = H_k(i,j) * f(i,j),\ 1 \le k \le N, \qquad (3)$$

Where * denotes the associated filtering operation. Next, subtract each processed image, g_k *(i, j), 1d” k d” N*, from *f(i,j)* to extract representative noise samples, $w_k(i,j)$, corresponding to each type of noise:

$$w_k(i,j) = f(i,j) - g_k(i,j),\ 1 \le k \le N. \qquad (4)$$

Next, estimate some simple statistical features from $w_k(i,j),\ 1 \le k \le N,$ and then classify the noise into one of N known classes using PNN.

III. IMPLEMENTATION

In this paper, we consider four different types of commonly occurring image noise, namely, non gaussian, gaussian, speckle, and salt-and-pepper noise. Among these four types, speckle noise is of multiplicative type, whereas the other three are additive in nature. The filters selected for the above four types of noise are wiener filter for uniform or gaussian white noise, homomorphic filter for speckle noise, and median filter for salt-and-pepper noise. Also, the statistical features studied here include “kurtosis” and “skewness”. Table I lists the “kurtosis” and “skewness” values, and the selected filters for the four types of noise.

TABLE I.
KURTOSIS, SKEWNESS AND FILTERS SELECTED FOR FOUR TYPES OF NOISE

Noise Type	Kurtosis	Skewness	Selected Filter
Gaussian	2.8741	0.0320	Wiener Filter
Speckle	2.6953	0.2066	Homomorphic Filter
Salt-and-pepper	30.240	1.2400	Median Filter
Non-Gaussian	2.4184	-0.0191	Wiener Filter

From Table I, we can see that different type of noise have different kurtosis or skewness values and those differences can be used to identify the noise type. Kurtosis is a measure of how outlier-prone a distribution is. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have kurtosis less than 3. Skewness is a measure of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right. The skewness of the normal distribution (or any perfectly symmetric distribution) is zero. The kurtosis and skewness

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of a distribution is defined as

$$K = E(x-\mu)^4/\sigma^4 \qquad (5)$$
$$S = E(x-\mu)^3/\sigma^3 \qquad (6)$$

Where μ is the mean of x, σ is the standard deviation of x, and $E(t)$ represents the expected value of the quantity t. `skewness` computes a sample version of this population value.

A. Extraction of Noise Samples from Input Noisy Image .

First, the three selected filters, Wiener filter, homomorphic filter, and median filter, are applied to the noisy image *f (i, j)* to get three different estimates $\hat{y}(i,j)$ for the original image *y (i, j)* as follows:

$$\hat{y}_{wiener}(i,j) = f(i,j) * H_{wiener}(i,j) \qquad (7)$$
$$\hat{y}_{median}(i,j) = f(i,j) * H_{median}(i,j) \qquad (8)$$
$$\hat{y}_{homo}(i,j) = Exp\,[\log(f(i,j)) * H_{Wiener}(i,j)] \qquad (9)$$

Where, the symbol * above denotes the associated spatial filtering operations. Then we get three noise estimates based on the outputs from the three filters as follows:

$$\omega_{wiener} = f(i,j) - \hat{y}_{wiener}(i,j) \qquad (10)$$
$$\omega_{median} = f(i,j) - \hat{y}_{median}(i,j) \qquad (11)$$
$$\omega_{homo} = f(i,j) / \hat{y}_{homo}(i,j) \qquad (12)$$

Next, the noise estimates obtained in equations (10)-(12) are used to identify the noise type.

B. Estimation of Some of Statistical Features.

In our proposed method, we are extracting two features namely Kurtosis and Skewness. These values are used to evaluate how close ω_{Wiener} is to Gaussian or uniform white noise, ω_{Median} is to salt-and-pepper noise, and ω_{Homo} is to speckle noise. To measure these similarities, we need some expected reference values to compare with. The expected reference values can be obtained by filtering the appropriate noise sequences and evaluating the Kurtosis and Skewness of the filter outputs. For instance, the procedure to obtain the expected reference values corresponding to salt-and-pepper noise, we do the following:

- First generate training sequences of Salt- and-Pepper noise.
- Filter each noise sequence through the median filter
- Then estimate the Kurtosis and Skewness of each filtered noise sequence and compute their average to yield the reference values of Kurtosis and Skewness for the salt-and-pepper noise.

C. PNN for Classification

A typical structure of PNNs is organized into a multilayered feed forward network with four layers: Input layer, pattern layer, summation layer and, Output layer. The input layer accepts input vectors. The non-linear dot product processing of input vectors and weight vectors is implemented in the pattern layer. The pattern layer is the core of a PNN. During training, the pattern vectors in the training set are simply copied to the pattern layer of the PNN. The classified samples probabilities are calculated in the summation layer. The output layer is a threshold discriminator that decides which of its input from the summation units is the maximum, and finally output classified results. The typical PNN architecture for the proposed method is shown below and consists of following:

- No of input nodes = 6
- No of nodes in pattern layer = 8
- No of nodes in summation layer = 4
- No of nodes in decision layer = 1

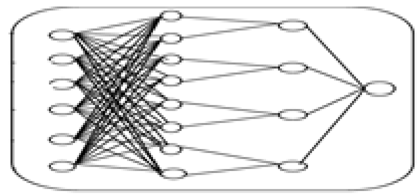

Figure 2. PNN architecture for proposed method

The three filters wiener filter, median filter and homomorphic filter are applied to the given noisy input image to get three values of kurtosis and three values of skewness. These six features are given as input to the neural network and then the network is trained to identify the type of noise that affected the image. The output layer decides which of its input from the summation units is the maximum, and finally outputs classified results.

IV. EXPERIMENTAL RESULTS

All experiments were carried out using Matlab. Matlab function “imnoise” is used to generate Gaussian white noise, speckle noise and salt-and-pepper noise. We have conducted simulations on different image sequences. Figures (3a)-(3d) represent one of the noisy image sequences as an example. With four different noise inputs, the calculated kurtosis, skewness and identified noise types are shown in Table II.

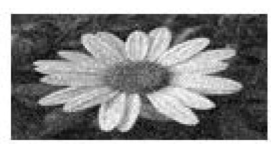

Fig: 3a

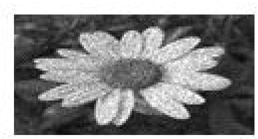

Fig: 3b

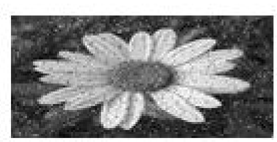

Fig: 3c

Fig: 3d

Figures (3a)-(3d): Clockwise from left (Gaussian white noise, speckle noise, salt and pepper noise, non- Gaussian white noise)

We also conducted testing for the same training set to different images by adding different percentage of noise for all the four types. The obtained results are shown in table III and the result of %of noise vs. accuracy is plotted as shown in figure 4. From figure 4, we can notice that the percentage of accuracy for classifying different types of noise is efficient for less percentage of noise. But since the values of kurtosis and skewness will vary by adding more noise, the performance at higher rate of noise decreases.

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TABLE II.
AN EXAMPLE OF KURTOSIS, SKEWNESS AND IDENTIFIED NOISE TYPES

Noise input	Std… Kurtosis	Std… Skewnes	Calc… Kurtosis	Calc… Skewness	Noise type
Gaussian	2.8741	0.0320	2.7058	0.0487	1
Speckle	2.6953	0.2066	2.8958	0.1322	2
Salt and Pepper	30.2402	1.2400	29.9806	1.8384	3
Non Gaussian	2.4184	-0.0191	2.6187	-0.0187	4

V. CONCLUSION

A neural network based technique for identifying the type of noise present in a noisy image is proposed in this paper. The proposed method exhibits fast training process and does not require any assumption in the given images such as homogeneous areas etc. The proposed technique can be used with a variety of de-noising filters. The results of simulation studies seem to indicate that the method is capable of accurately determining the type of noise.

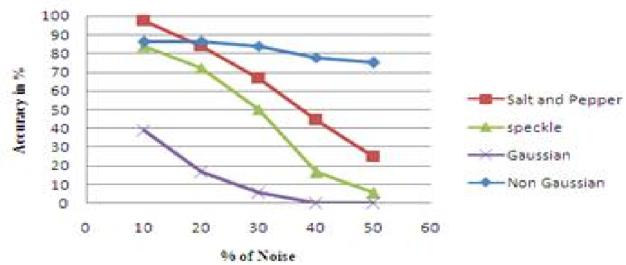

Figure 4. % of Noise vs. Accuracy

TABLE III.
ACCURACY OF FOUR TYPES OF NOISE

% of Noise	Images Tested	Salt and Pepper Noise			Speckle Noise			Gaussian Noise			Non-Gaussian Noise		
		Correct	Wrong	Accuracy	Correct	Wrong	Accuracy	Correct	Wrong	Accuracy	Correct	Wrong	Accuracy
10	36	35	01	97.2	30	06	83.8	14	22	38.8	31	05	86.1
20	36	30	06	83.8	26	10	72.2	06	30	16.6	31	05	86.1
30	36	24	12	66.6	18	18	50	02	34	5.5	30	06	83.8
40	36	16	20	44.4	06	30	16.6	00	36	00	28	08	77.7
50	36	09	27	25	02	34	5.50	00	36	00	27	09	75

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